How Does Provider Entry and Exit Affect Patient Outcomes?

A Chandra, Harvard and NBER
M Dalton, NBER
DO Staiger, Dartmouth and NBER

Disclosures: Staiger (ArborMetrix), Chandra (CBO Panel of Health Advisors)

More Disclosures

- This is an early-stage research program
- Today's focus will be on the effect of hospital-closures on patient outcomes
- Later versions look at hospital entry and the effect of surgeon migration on patient outcomes

Save our Hospital!









What do we know about closures?



The NEW ENGLAND JOURNAL of MEDICINE

Perspective

JUNE 28, 2012

The Health Care Jobs Fallacy

Katherine Baicker, Ph.D., and Amitabh Chandra, Ph.D.

ACCESS TO CARE

By Karen E. Joynt, Paula Chatterjee, E. John Orav, and Ashish K. Jha

Hospital Closures Had No Measurable Impact On Local Hospitalization Rates Or Mortality Rates, 2003–11

ABSTRACT **The Affordable Care Act (ACA) set in motion payment changes that could put pressure on hospital finances and lead some hospitals to close. Understanding the impact of closures on patient care and outcomes is critically important. We identified 195 hospital closures in the United States between 2003 and 2011. We found no significant difference between the change in annual mortality rates for patients living in hospital service areas (HSAs) that experienced one or more closures and the change in rates in matched HSAs without a closure (5.5 percent to 5.2 percent versus 5.4 percent to 5.4 percent, respectively). Nor was there a significant difference in the change in all-cause mortality rates following hospitalization (9.1 percent to 8.2 percent in HSAs with a closure versus 9.0 percent to 8.4 percent in those without a closure). HSAs with a closure had a drop in readmission rates compared to controls (19.4 percent to 18.2 percent versus 18.8 percent to 18.3 percent). Overall, we found no evidence that hospital closures were associated with worse outcomes for patients living in those communities. These findings may offer reassurance to policy makers and clinical leaders concerned about the potential acceleration of hospital closures as a result of health care reform.**

Does Hospital Closure Affect Local Patients?

- **Impact should depend on quality of closing hospital and its market share**
  - Closing high-mortality hospital may be good for patients?

- **Our Enterprise: Test whether the quality of the closing hospital predicts patient outcomes in affected zipcodes**
  - Implications for policies on closures and selective referral
  - Allows us to validate measures like risk-adjusted mortality (like Chetty et al, 2013; Doyle et al, 2017)

Market Learning affects allocation…making this hard

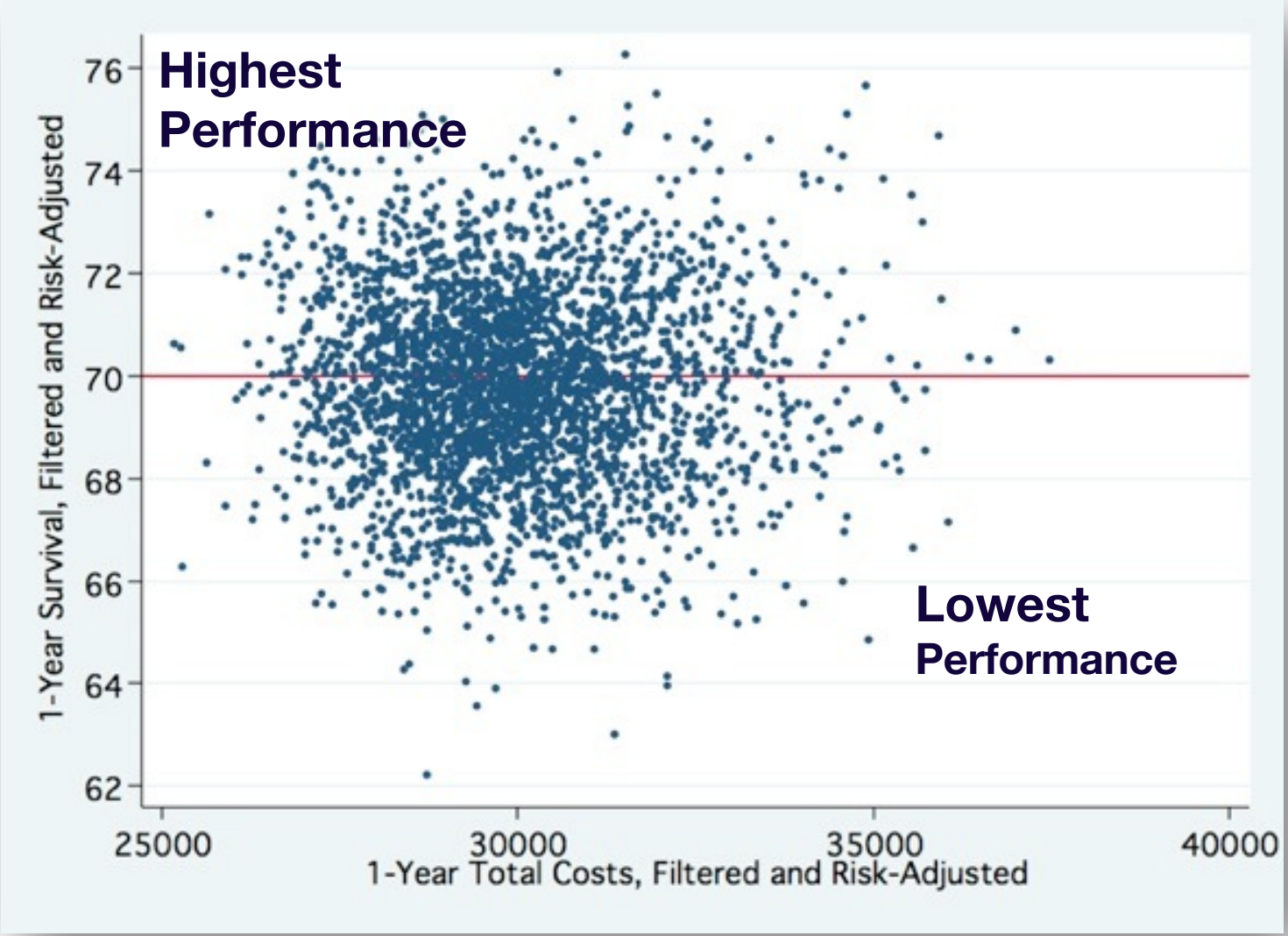
American Economic Review 2016, 106(8): 2110–2144
http://dx.doi.org/10.1257/aer.20151080

Health Care Exceptionalism? Performance and Allocation in the US Health Care Sector†

By Amitabh Chandra, Amy Finkelstein, Adam Sacarny, and Chad Syverson*

The conventional wisdom for the health care sector is that idiosyncratic features leave little scope for market forces to allocate consumers to higher performance producers. However, we find robust evidence across several different conditions and performance measures that higher quality hospitals have higher market shares and grow more over time. The relationship between performance and allocation is stronger among patients who have greater scope for hospital choice, suggesting that patient demand plays an important role in allocation. Our findings suggest that health care may have more in common with "traditional" sectors subject to market forces than often assumed. (*JEL* I11, L25)

Large Variation in Risk-Adjusted Mortality Across Hospitals, Is it causal…or does it reflect unmeasured confounders?



Source: Chandra, Staiger and Skinner (IOM, 2010)

Outline

- Overview of data & closures
- Overview of hospital performance measures
  - Quality
  - Utilization
  - Cost
- Test whether performance measures predict impact of hospital closure on patients living in affected zipcodes

Data

- 100% Medicare 65+ inpatient claims,
  1992-2013, linked to death records & patient zip codes.

- We stack 5 patient admission cohorts:
  4.6m AMI, 8.4m Pneumonia, 7.1m CHF, 5.4m stoke,
  3.8m hip fractures. Total of **29.3 million** admissions
  aggregated to the zipcode-year-cohort level.

- Identify 642 hospital closures from The Dartmouth Institute (TDI) closure file, cross-validated by hand, using the google maps API, claims and AHA data.
  http://users.nber.org/~daltonm/hclose/

Hospital closures in our data

	ami	hip	chf	pnu	strk
Total closures					
TDI closure	684	684	684	684	684
# of closures dropped	55	55	55	55	55
Closures used, 1994-2011	629	629	629	629	629
Closures used in analysis					
# closures in event set	447	411	476	491	433
Total # patients (1000s)	4548	3821	7114	8410	5362
# treated in closed (1000s)	102	87	195	248	125
Break down by year of closure					
1994-1996	100	89	101	102	89
1997-2000	139	124	149	154	142
2001-2004	102	93	104	105	92
2005-2008	77	80	87	94	79
2009-2011	29	25	35	36	31

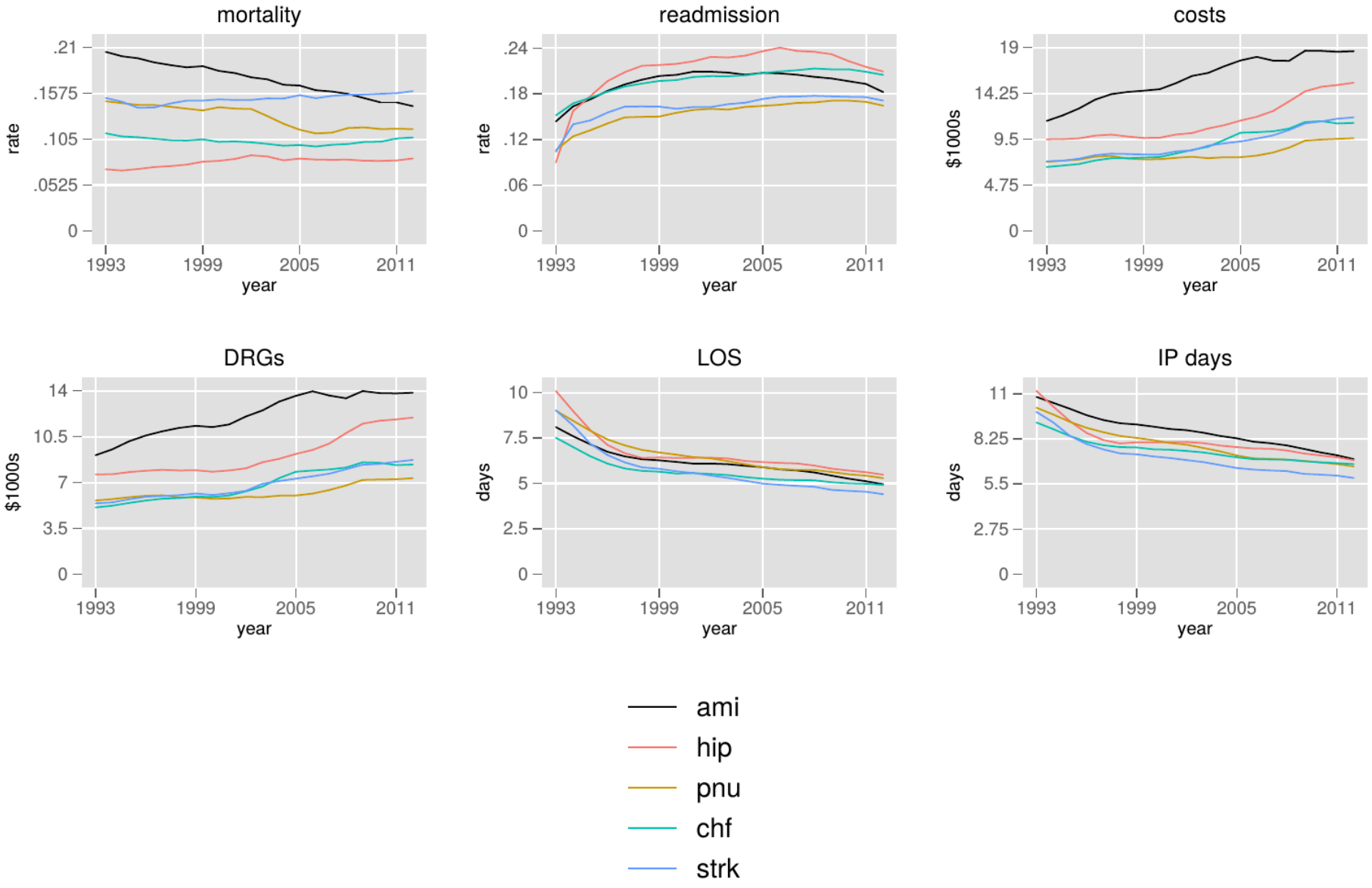
Outcomes

- We consider six standard measures:
  - **Quality measures:** 30 day mortality, 30-day readmission rates
  - **Cost measures:** 30 day hospital DRG cost (with no adjustments for things like local wage level, minority serving hospital), 30 day inpatient costs (includes hospital + physician services)
  - **Utilization measures:** Length of stay, number of hospital days in the first 30 days.

Episode level characteristics

	all	closed	not
Patient level characteristics			
Patient age	80.06	80.28	80.05
Proportion female	0.58	0.61	0.58
Proportion white	0.89	0.80	0.89
# of comorbidities	1.18	1.15	1.18
non-cost outcomes			
30 day mortality	0.13	0.14	0.13
30 day readmission	0.18	0.18	0.18
index length of stay (days)	6.16	7.66	6.12
Total IP days within 30 day	7.89	9.34	7.86
cost outcomes			
30 day inpatient cost	9969	9839	9972
30 day inpatient DRG	7711	6928	7729
observations	29255428	674464	28580964

Trends in Patient Outcome Measures



Basics of Risk Adjusted Performance

- Hospital performance measures compare observed patient outcomes to a counterfactual expectation
- Difference between observed and expected outcome, averaged over hospital's patients
- Expected outcome is average outcome for patients who looked similar at admission, based on age-sex-race and comorbidities
- Note that this hospital-level residual is super noisy→ need empirical bayes!

Predicting Hospital Performance

- Estimate outcomes regression for patient *i* in hospital *j* in year *t*:

  $Y_{ijt} = \beta X_{it} + \alpha Ln(volume_{jt}) + \mu_{jt} + \varepsilon_{ijt}$

  Hospital effect = $\alpha Ln(volume_{jt}) + \mu_{jt}$

- Hospital residual $\bar{Y}_{jt}$ is average difference between observed and expected outcome:

$$\overbrace{Y_{ijt}}^{Observed} - \overbrace{(\hat{\beta} X_{it} + \hat{\alpha} Ln(volume_{jt}))}^{Expected}$$

- Estimate error components: $\bar{Y}_{jt} = \mu_{jt} + \bar{\varepsilon}_{jt}$

  - let $corr(\mu_{jt}, \mu_{jt-k}) = r_k$, $\text{var}(\mu_{jt}) = \sigma_\mu$ (stationary, drift)
  - without drift ($r_k = 1$); this is the `mixed` command in Stata

- BLUP posterior mean: $\hat{\alpha} Ln(volume_{jt}) + \text{E}(\mu_{jt} | \vec{Y}_j^{-t})$

  (volume component + EB prediction of hospital residual)

Prediction in simple case

- Idea is to use average residual from one year ($\bar{Y}_{js}$) to predict hospital performance in a different year:

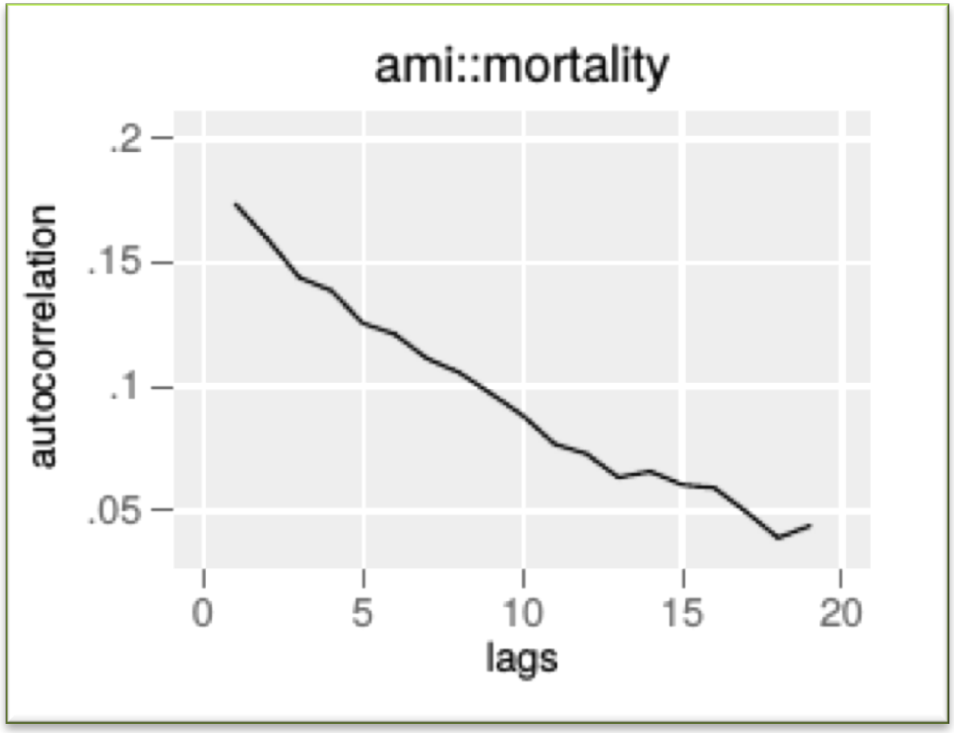
  Empirical Bayes Prediction = $\mathrm{E}\left(\mu_{jt}|\vec{Y}_j^{-t}\right) = \gamma_j \bar{Y}_{js}$

- Optimal weights (γ_j) analogous to regression coefficients:

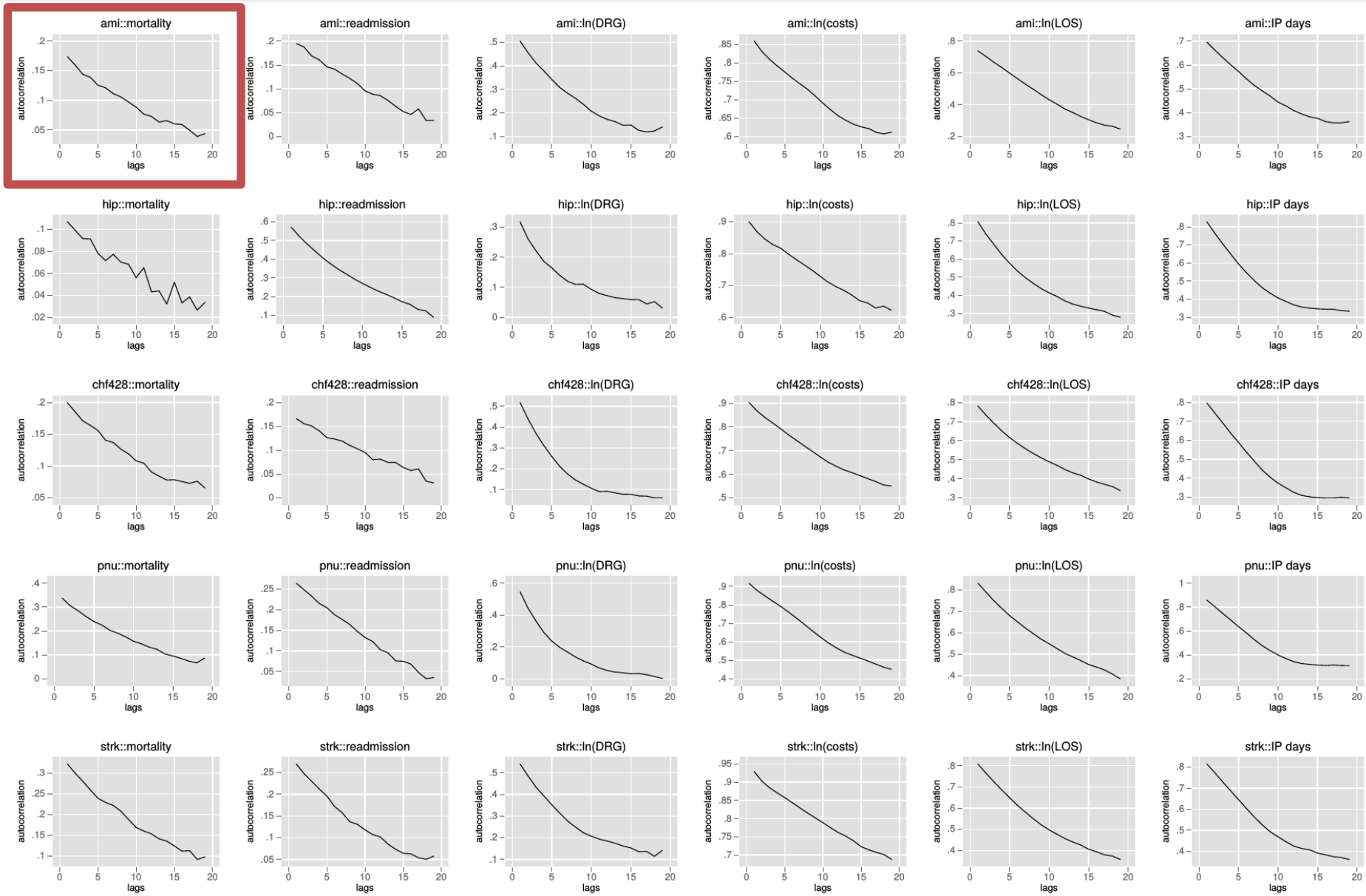
  γ_j = Cov(μ_{jt}, $\bar{Y}_{js}$)/Var($\bar{Y}_{js}$)
  = Cov(μ_{jt}, μ_{js})/ Var($\bar{Y}_{js}$)
  = {Cov(μ_{jt}, μ_{js})/Var(μ_{js})}*{Var(μ_{js})/ Var($\bar{Y}_{js}$)}
  = r_{t-s}* reliability of $\bar{Y}_{js}$

- So weight placed on average residual from other years depends on
  - Correlation of persistent component between t, t-k = r_k
  - Reliability with which average residual is estimated in t-k, which varies by hospital based on volume

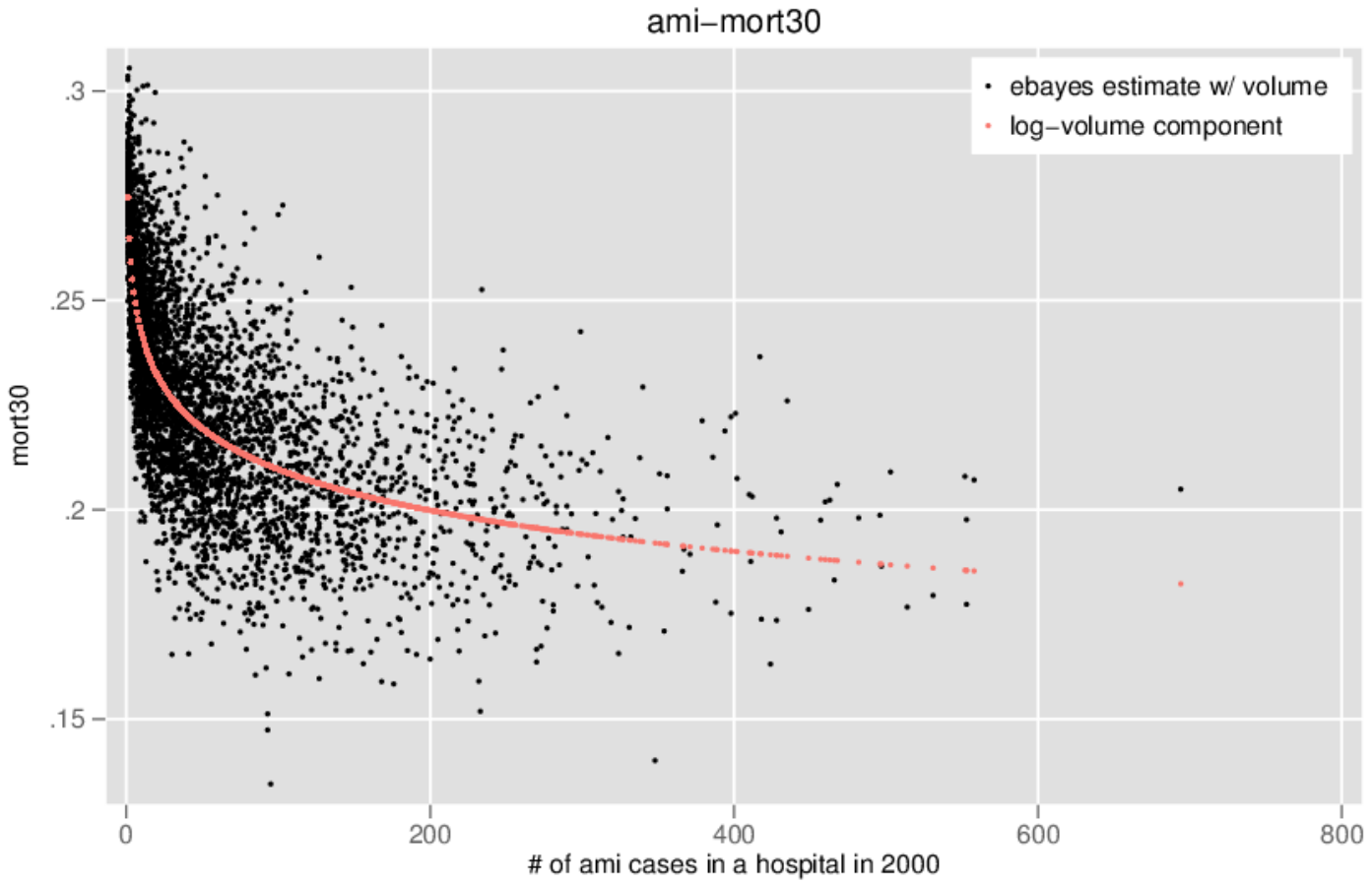
Allowing for Drift is important



Declining autocorrelation (drift) in all outcomes and cohorts

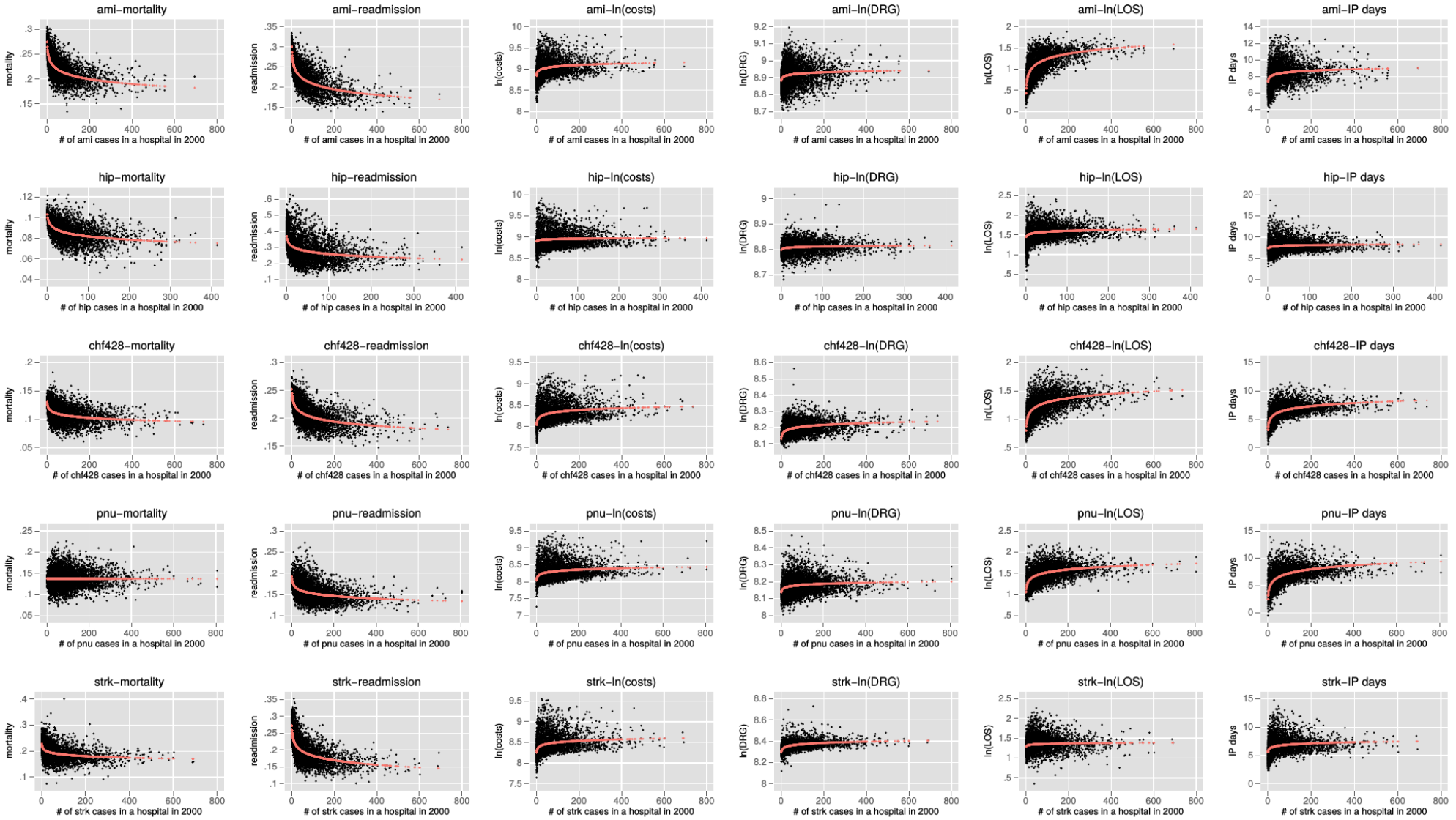


Predictions of Hospital 30-day AMI Mortality, 2000



Example Empirical Bayes predictions of hospital mortality rate in 2000, accounting for volume and drift, using data from 1992-1999 & 2003-2013

Predictions for all outcomes & cohorts, 2000



Test predictions following Chetty et al. (2013)

$Reduced\ Form$:

$$\Delta Y_{zip,t} = \beta_0 + \beta_1 \Delta Expected_{zip,t} + Year * Cohort_{zip,t} + \varepsilon_{zip,t}$$

- $\Delta Y_{zip,t}$ = change from year *t*-1 to *t+1* in cohort specific outcome, i.e. 30-day mortality rate, in each zip code (based on patient zip in t-1). Y is residualized (through risk adjustment)

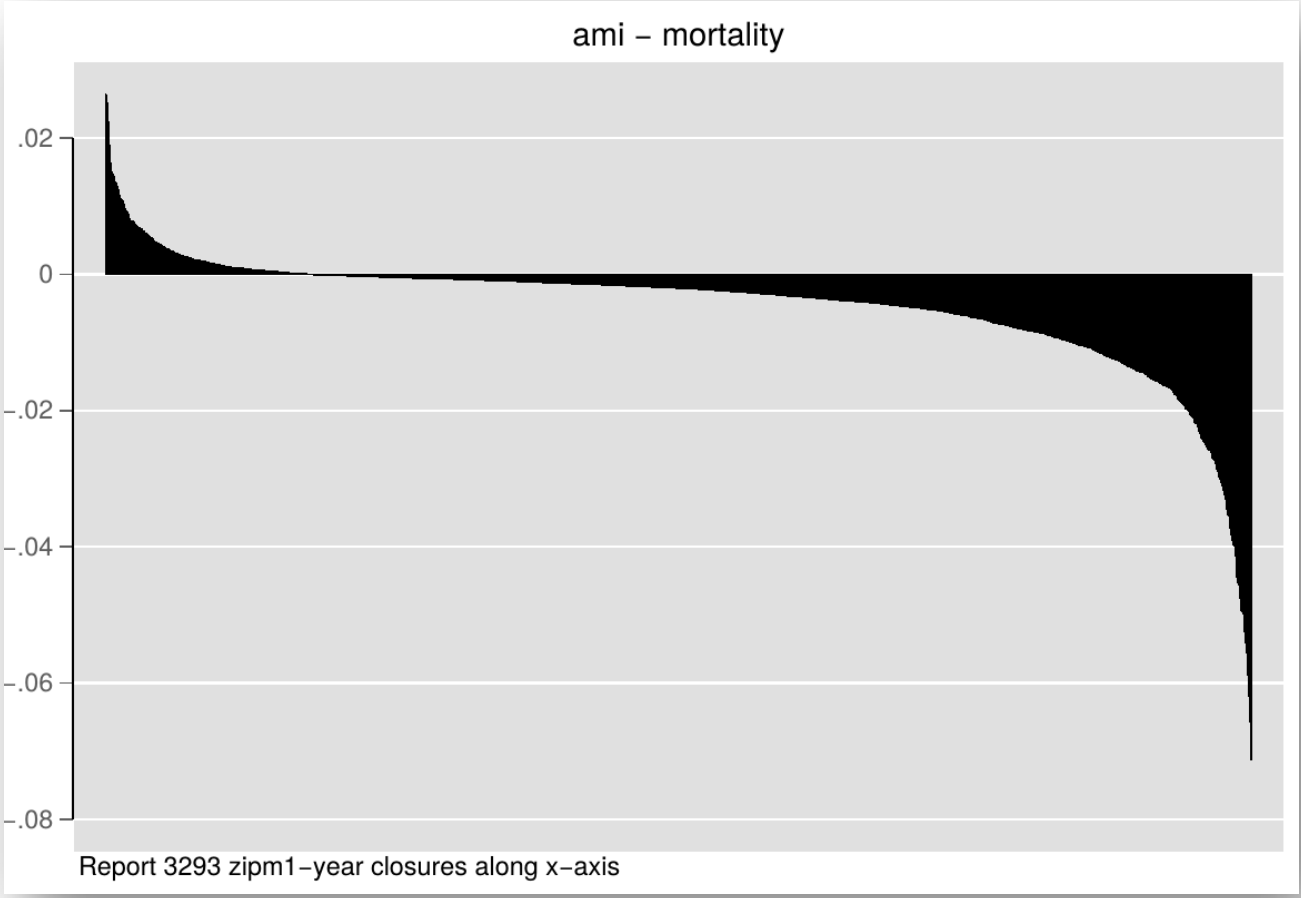
- $\Delta Expected_{zip,t}$ = (closed hospital market share in zip in t-1) *
  (other hospitals' average predicted mortality
  - closed hospital's predicted mortality)
  = expected mortality change due to hospital closure in t

- Use EB prediction (with drift) of hospital mortality rates based on volume in t-1 & mortality data not including (t-1, t, t+1).

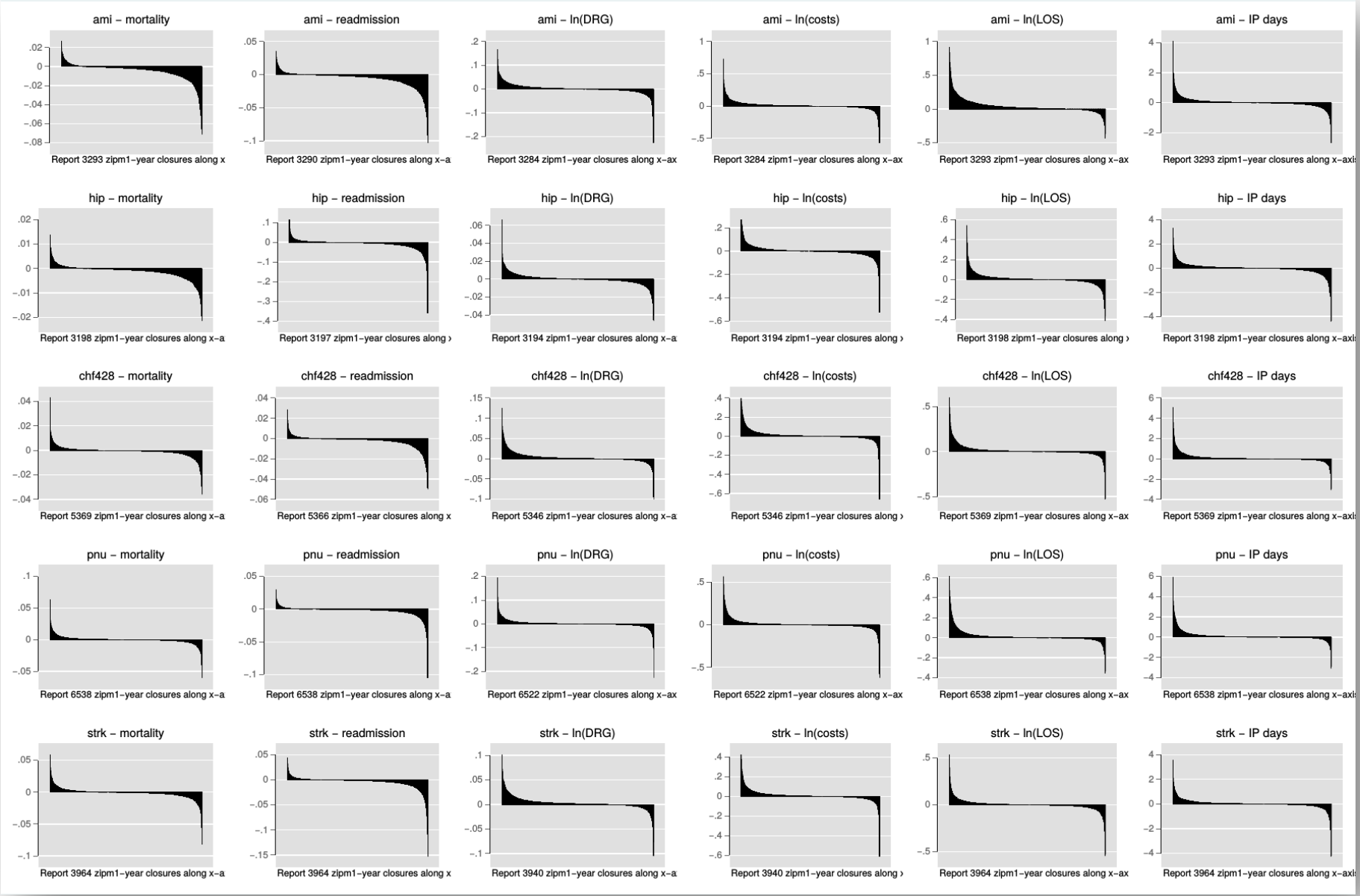
- 2SLS version, use $\Delta Expected_{zip,t}$ as instrument for $\Delta Q_{zip,t}$, where:
  $\Delta Q_{zip,t}$ = change in predicted outcome/cost based on weighting by actual zip code level market shares in t-1 & t+1. (b_{IV}=1 implies forecast unbiased)

Range of Expected Change In Mortality From Closures

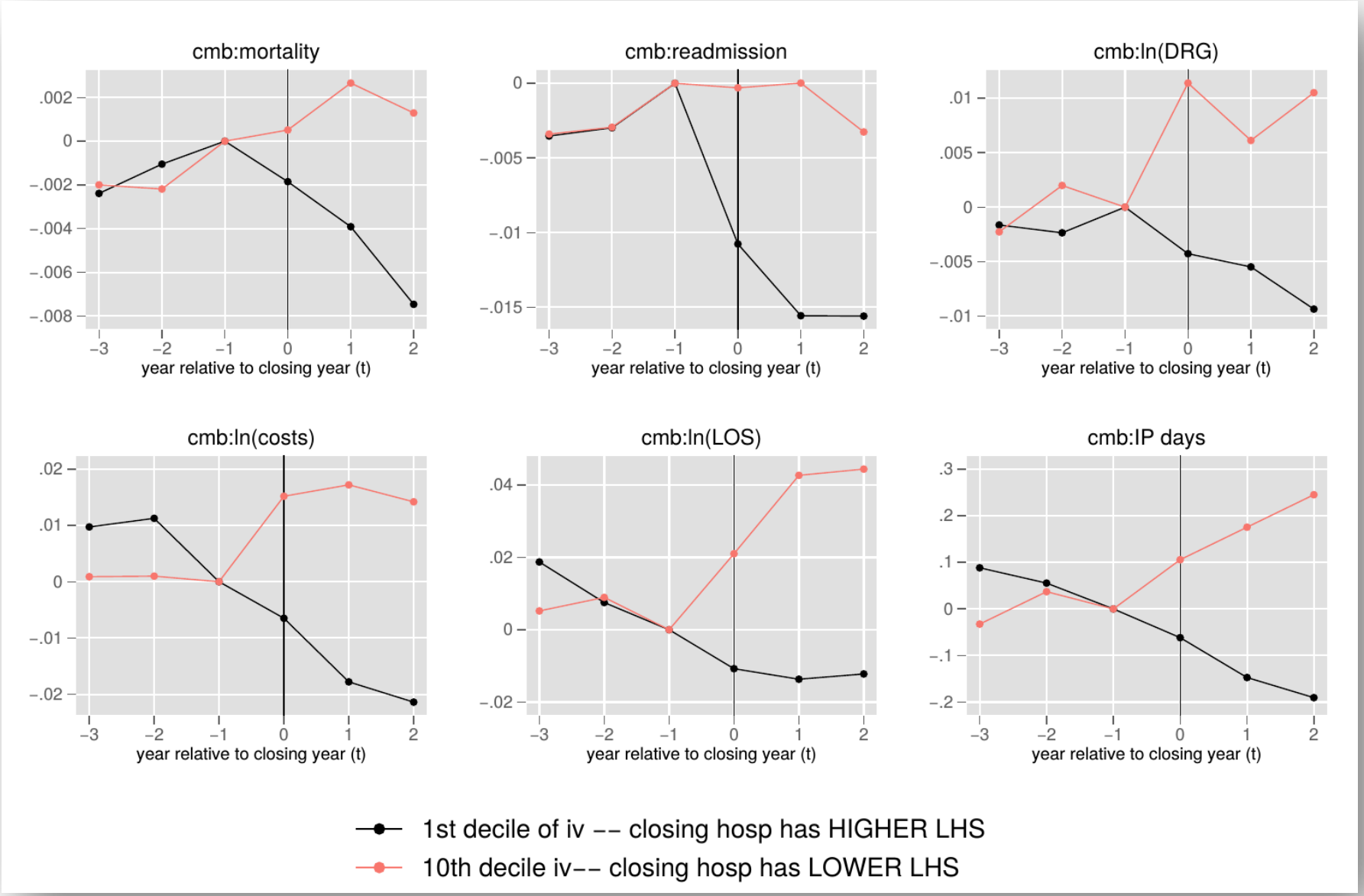
- Distribution of $\Delta Expected_{zip,t}$, a measure of the impact of closure on a zipcode



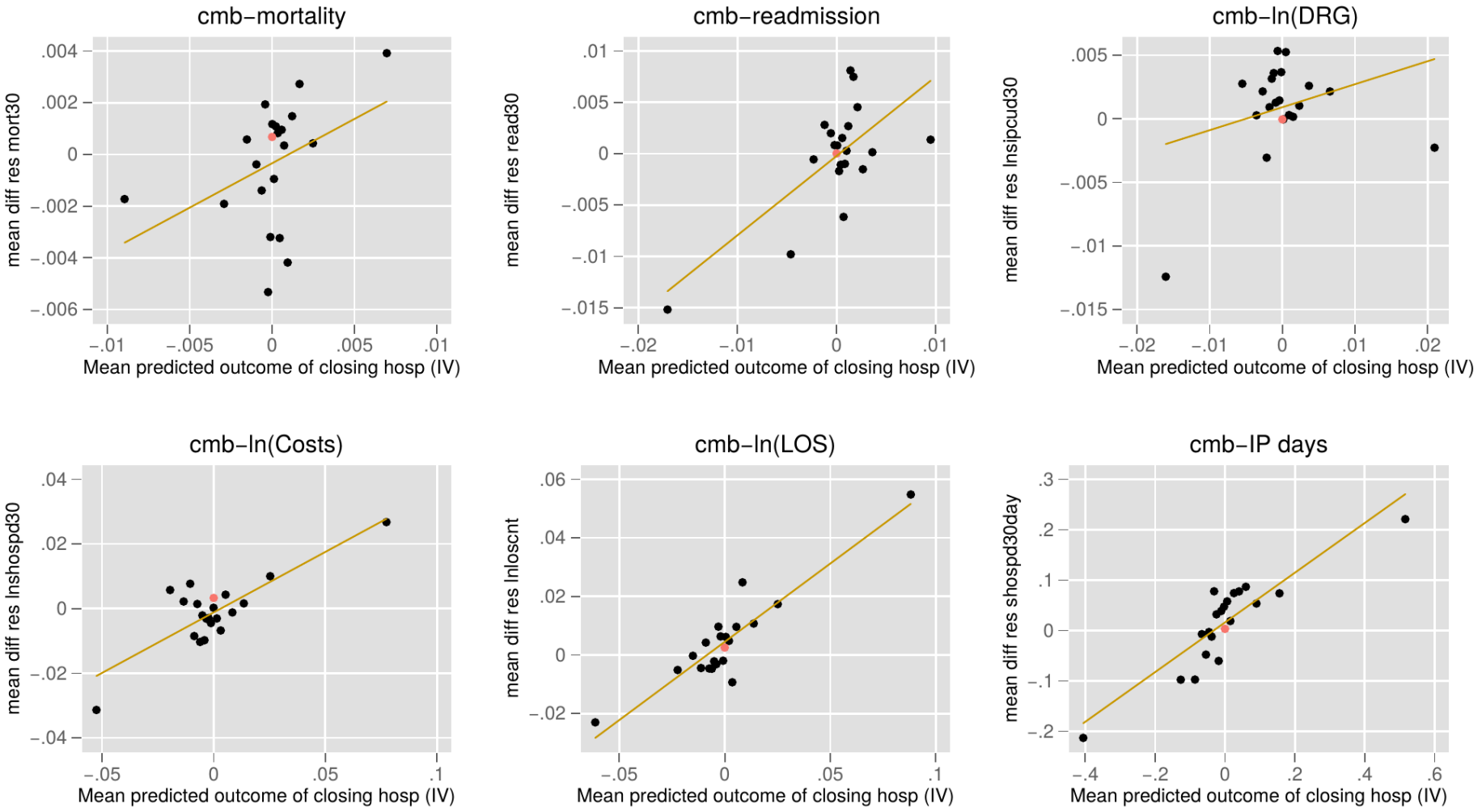
Range of Expected Change From Closures-all



Event Study: Change in patient outcomes for zipcodes expected to be most positively and negatively affected by closure (deciles)



Reduced Form Plot of Actual on Expected Change (20 bins)



OLS and 2SLS of Predicted Mortality Changes

	$\Delta mortality_{zip,t}$				$\Delta readmission_{zip,t}$			
	(1) 1st stage β / se	(2) reduced form β / se	(3) 2SLS β / se	(4) OLS β / se	(5) 1st β / se	(6) reduced form β / se	(7) 2SLS β / se	(8) OLS β / se
$\Delta EXP_{zip,t}$	0.638***	0.518**			0.651***	0.701***		
	(0.037)	(0.182)			(0.056)	(0.124)		
Δ $Q_{zip,t}$			0.812**	-0.030			1.076***	0.210***
			(0.285)	(0.023)			(0.187)	(0.022)
YRxCohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2174004	2174004	2174004	2174004	2133264	2133264	2133264	2133264
R^2	0.006	0.000	−0.003	0.000	0.007	0.000	−0.005	0.000
RMSE	0.009	0.136	0.136	0.136	0.014	0.166	0.166	0.166

Note: Predict hospital outcome or costs using pre and post data. Standard errors clustered at patient HRR level in t-1.

$\Delta mort30_{zip,t}$ =change in residualized 30 day mortality

$\Delta read30_{zip,t}$ =change in residualized 30 day readmission

OLS and 2SLS of Predicted Mortality Changes

	$\Delta ln(LOS)_{zip,t}$				$\Delta IPdays_{zip,t}$			
	(1) 1st stage	(2) reduced form	(3) 2SLS	(4) OLS	(5) 1st	(6) reduced form	(7) 2SLS	(8) OLS
	β / se	β / se	β / se	β / se	β / se	β / se	β / se	β / se
$\Delta EXP_{zip,t}$	0.655***	0.517***			0.699***	0.601***		
	(0.037)	(0.060)			(0.047)	(0.083)		
Δ $Q_{zip,t}$			0.790***	0.626***			0.859***	0.549***
			(0.093)	(0.008)			(0.119)	(0.012)
YRxCohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2174000	2174000	2174000	2174000	2174004	2174004	2174004	2174004
R^2	0.010	0.000	0.023	0.025	0.010	0.000	0.012	0.018
RMSE	0.074	0.294	0.291	0.290	0.540	2.215	2.201	2.195

Note: Predict hospital outcome or costs using pre and post data. Standard errors clustered at patient HRR level in t-1.

$\ln(los_{zip,t})$ =change in residualized natural log length of stay of the index event

$\Delta hospday30_{zip,t}$ =change in residualized number of days spent at hospital in first 30 after index

OLS and 2SLS of Predicted Mortality Changes

	$\Delta ln(cost)_{zip,t}$				$\Delta ln(DRG)_{zip,t}$			
	(1) 1st stage β / se	(2) reduced form β / se	(3) 2SLS β / se	(4) OLS β / se	(5) 1st β / se	(6) reduced form β / se	(7) 2SLS β / se	(8) OLS β / se
$\Delta EXP_{zip,t}$	0.561***	0.342***			0.584***	0.329**		
	(0.030)	(0.069)			(0.040)	(0.167)		
Δ $Q_{zip,t}$			0.610***	0.631***			0.564**	0.319***
			(0.109)	(0.025)			(0.286)	(0.013)
YRxCohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2131344	2131344	2131344	2131344	2131342	2131342	2131342	2131342
R^2	0.004	0.000	0.035	0.035	0.004	0.000	0.001	0.002
RMSE	0.066	0.222	0.218	0.218	0.025	0.197	0.197	0.197

Note: Predict hospital outcome or costs using pre and post data. Standard errors clustered at patient HRR level in t-1.

$\Delta \ln(ipcost30)_{zip,t}$ =change in natural log of residualized 30 day short-term acute inpatient costs

$\Delta \ln(ipcostutiliz30)_{zip,t}$ =change in natural log of residualized 30 day short-term acute inpatient costs using DRG base payment

Adding closed hospital market share in period t-1

	$\Delta mortality_{zip,t}$				$\Delta readmission_{zip,t}$			
	(1) 1st stage β / se	(2) reduced form β / se	(3) 2SLS β / se	(4) OLS β / se	(5) 1st β / se	(6) reduced form β / se	(7) 2SLS β / se	(8) OLS β / se
$\Delta EXP_{zip,t}$	0.608***	0.595**			0.592***	0.690***		
	(0.040)	(0.190)			(0.053)	(0.133)		
Closed mkt share	-0.003***	0.007	0.010**	0.004	-0.006***	-0.001	0.006	-0.009*
	(0.001)	(0.005)	(0.005)	(0.005)	(0.001)	(0.005)	(0.006)	(0.005)
Δ $Q_{zip,t}$			0.980**	-0.030			1.164***	0.210***
			(0.314)	(0.023)			(0.234)	(0.022)
YRxCohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2174004	2174004	2174004	2174004	2133264	2133264	2133264	2133264
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RMSE	0.009	0.136	0.136	0.136	0.014	0.166	0.166	0.166

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Adding closed hospital market share in period t-1

	$\Delta ln(LOS)_{zip,t}$				$\Delta IPdays_{zip,t}$			
	(1) 1st stage β / se	(2) reduced form β / se	(3) 2SLS β / se	(4) OLS β / se	(5) 1st β / se	(6) reduced form β / se	(7) 2SLS β / se	(8) OLS β / se
$\Delta EXP_{zip,t}$	0.607***	0.511***			0.656***	0.606***		
	(0.031)	(0.061)			(0.037)	(0.083)		
Closed mkt share	0.041***	0.006	-0.029*	-0.014	0.319***	-0.042	-0.337**	-0.163
	(0.009)	(0.013)	(0.015)	(0.013)	(0.065)	(0.108)	(0.119)	(0.110)
Δ $Q_{zip,t}$			0.841***	0.626***			0.924***	0.550***
			(0.105)	(0.008)			(0.125)	(0.012)
YRxCohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2174000	2174000	2174000	2174000	2174004	2174004	2174004	2174004
R^2	0.010	0.000	0.022	0.025	0.011	0.000	0.010	0.018
RMSE	0.074	0.294	0.291	0.290	0.540	2.215	2.204	2.195

Note: Predict hospital outcome or costs using pre and post data. Standard errors clustered at patient HRR level in t-1.

$\ln(los_{zip,t})$ =change in residualized natural log length of stay of the index event

$\Delta hospday30_{zip,t}$ =change in residualized number of days spent at hospital in first 30 after index

Adding closed hospital market share in period t-1

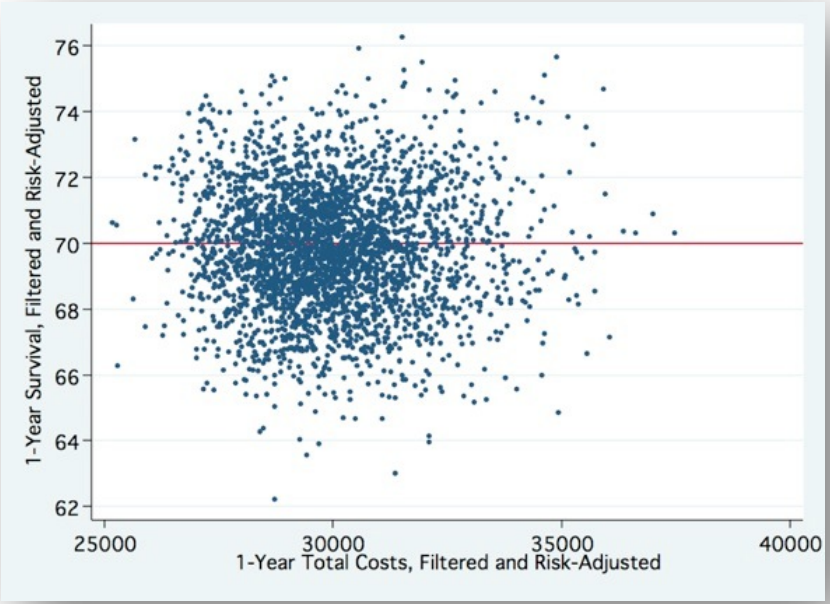
	$\Delta ln(cost)_{zip,t}$				$\Delta ln(DRG)_{zip,t}$			
	(1) 1st stage β / se	(2) reduced form β / se	(3) 2SLS β / se	(4) OLS β / se	(5) 1st β / se	(6) reduced form β / se	(7) 2SLS β / se	(8) OLS β / se
$\Delta EXP_{zip,t}$	0.550***	0.372***			0.547***	0.337**		
	(0.032)	(0.075)			(0.038)	(0.171)		
Closed mkt share	0.007	-0.017	-0.022*	-0.020**	0.008***	-0.002	-0.007	-0.003
	(0.007)	(0.012)	(0.011)	(0.010)	(0.002)	(0.006)	(0.007)	(0.006)
Δ $Q_{zip,t}$			0.678***	0.631***			0.617**	0.319***
			(0.121)	(0.025)			(0.307)	(0.013)
YRxCohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2131344	2131344	2131344	2131344	2131342	2131342	2131342	2131342
R^2	0.004	0.000	0.035	0.035	0.004	0.000	0.000	0.002
RMSE	0.066	0.222	0.218	0.218	0.025	0.197	0.197	0.197

Note: Predict hospital outcome or costs using pre and post data. Standard errors clustered at patient HRR level in t-1.

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$\Delta \ln(ipcostutiliz30)_{zip,t}$ =change in natural log of residualized 30 day short-term acute inpatient costs using DRG base payment

Summing Up



- We validate hospital performance measures
  - Measures predict causal effects
  - Quality & utilization measures are forecast unbiased
  - Cost measures overstate differences in causal effects
- New evidence on impact of hospital closures
  - Little effect of closing per se (just like earlier literature)
  - Heterogeneity: Closing under-performing hospitals improves patient outcomes
- Large implications for narrow networks & selective referral
- Future work looks at hospital entry and surgeon movement